College Move-in and the Prices at the "Pumps"

A Senior Honors Thesis

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Introduction

Every year without fail thousands of students and parents descend on cities and towns across the nation to start a new year of higher education. The specific date or weekend that they come is filled with orientations, social gatherings, moving things into the dorm room, etc. After some tearful goodbyes, the parents begin to make the long trek back home. However, before they begin their journey, many of them realize that they are low on gasoline and pull into a gas station, unaware that the cheaper gas station was just down the street. Meanwhile, back at the university, many students are faced with the daunting task of learning which gas stations have the cheapest prices.

For this thesis, we have studied the prices of gasoline in college towns across the country during the big "move-in". While it might be supposed that prices would rise because of a demand increase, the reality might not be so simple. We discuss several different theories, such as the loss-leader model or the tourists-natives theory, which could predict different price movements during the move-in.

In our work, we sought to find out what gasoline prices would do in the face of a large increase in college students. The data was collected in the late summer and early fall of 2009 from gasoline stations within a roughly ten-mile radius of over fifty universities and colleges across the country. A difference-in-difference regression analysis of the data was used to compare the days that were impacted by the move-in effect with the other days in our sample. What was discovered was that the price of gasoline not only did rise on the move-in day, but also was higher for days or weeks before and after the official move-in. These somewhat surprising results may indicate that it took a long time for the uninformed students who had cars to figure out the price dispersion in the city.

In this paper, we will first look at the relevant literature surrounding the subject. Next, we will present the data and methods used for our tests. After that, we will present the results of our analysis. The conclusion will be the next and final section.

The Literature

A simple look at the supply-demand model of prices would suggest that when demand increases, *ceteris paribus*, the price will also rise and the market will remain in perfect equilibrium, however, this outcome is not always the case. If gas station managers are able to quickly increase volumes in response to even a small price increase then the short run supply curve would be effectively flat and there would be little to no change in prices on move-in day. In addition to the supply-demand model, there exist other price theories that provide alternative explanations for how prices could react to a demand change like the one during the move-in.

The tourists-natives model is one such model and is well-known in the economics field. The model assumes that there are two types of consumers: the natives (those who know what the prices are in a given market) and the tourists (those who do not). For the natives in our situation, the costs for buying gasoline would simply be the price (assuming there is no travel cost), because they do not need to spend time searching for the cheapest station. For the tourists, they must spend time searching for a gasoline station in addition to the price, which is commonly referred to as searching costs. These searching costs make it more likely for a tourist to settle for a higher-priced station rather than spending an unknown amount of time looking for the cheapest place. An increase in the amount of tourists would lead to higher incentives for other firms to increase their prices to take advantage of the tourists.

This is a very likely explanation for what will happen during the move-in boom. Parents and many incoming students probably have no idea of the gasoline price dispersion in the college city. Even after the parents leave for home, many students, whom drive and have no idea what station charges what price for gasoline, will remain in the city for an extended period. This could cause a prolonged move-in effect, where prices are high until most of the students learn the gasoline price dispersion. This is also an annual event, so it is very predictable for gasoline stations. However, it is unknown as to how many tourists will buy gasoline during the move-in. It is possible that only an insignificant number purchase gasoline, leading to no real change in prices.

Other alternative models focus on the possibility of a price decrease in the face of a rise in demand. Rotemberg and Saloner (1986) were among the first to build a model of countercyclical pricing based on collusion. They argued that, during a demand boom, the incentive to cheat on a collusion pact was high because of the greater possible profits gained from cheating. If a firm were to cheat, the response is almost always a retaliation of even lower prices, which would create a price war where the market would eventually fall to the zero-profit, competitive level. In order to prevent a business from cheating on their price agreement and the ensuing price war, the cartel will lower its agreed upon level to the point where the gains from cheating are less than the profits from colluding. On the other hand, when there is a demand bust, the possible profits from cheating on a collusive pact will decrease, which would allow the cartel to raise prices without fear of a firm breaking the pact.

A second paper, by Haltiwagner and Harrington (1991), amends Rotemberg and Saloner's work by bringing expectations into the mix. In their model, expectations of the firm on the direction that demand is heading determine whether to collude or to cheat. As long as demand is expected to rise a firm will still have strong incentives not to cheat because, by cheating, the firm would have to forego all of the increasingly higher future profits gained from a still increasing demand. The opportunity cost from the profits gained by keeping the pact would just be too much. When future demand is expected to decrease, however, the incentive to cheat grows. This is because future profits are expected to decrease through collusion. At some point the profits gained from cheating would outweigh the dwindling profits from colluding and the prices should drop. Borenstein and Shepard (1996) show some empirical support of this expectations argument in the retail gasoline market.

Chevalier, Kashyap, and Rossi (2003) use an altogether different explanation for countercyclical price behavior. They use a loss leader model to describe why prices may decrease during high demand. In this model, a retail firm will decrease the price on its most popular items in order to draw in customers. Once the consumers are at the store, they are more likely to make other, less cheap purchases other than just the one item for which they were looking. An example of this would be going to the store around Thanksgiving to take advantage of its sales on turkeys, but then decide to purchase a few bottles of Coke as well because it is convenient.

If the results were to show a price decrease, the next question that would need to be asked is which model best describes what happened. It is very well possible that either the loss leader model has the best explanation because of the similarities between a large retail store and a gasoline station. It is also just as likely that the collusion models are the best countercyclical explanation for the move-in effect because there has already been evidence shown for Haltwagner and Harrington's expectations model by Borenstein and Shepard.

The Data and Methodology

For this research, we wanted to see if gasoline prices changed over the move-in day. To do this, we needed to find college towns and cities where the move-in day shock should be large enough to be noticeable, if it existed at all. The criteria that we used to determine this were as follows: (1) they could not be located inside the Midwest because of the highly fluctuating price cycles found there[i] that could overshadow the effect caused by the move-in, (2) the city was not too big so that the sudden increase in demand would not go unnoticed, and (3) that the school was large enough to possibly make such an impact. Using these as guidelines, over fifty universities[ii] throughout the US were selected. The names of the schools, their zip codes, the size of the student body, and the cities in which they were located had been recorded for the data set.

It was also necessary to get the distances between each station and its school. The address of each university and the website *iTouchMap.com*[iii] were used to find the relative latitude and longitudes of each school. Next, the web page *MSN Auto Gas Price*[iv] gave information on the prices, zip codes, station ID's, and latitudes/longitudes of the closest thirty stations to each school with a few exceptions for some schools[v]. The price data extends from the middle of August to the middle of November 2009—about a three-month period—so that there was a wide range of data. It should be noted that not every station recorded prices for every day, so that the data is incomplete in some places. In fact, some stations recorded their daily prices so infrequently that it was decided that it would be better to remove them from the data set[vi]. The prices are recorded in cents per gallon ($2.50 = 250 cents). From all of the latitude/longitude information, distances from the university variables were generated that are measured in miles.

Lastly, the move-in date, or the day that the residence halls opened, was located for each university by searching through each school's website[vii]. However, it could not be determined when every school's move-in date was and instead the move-in date was listed as the Saturday before the first day of classes. That day was chosen because the weekend seemed to be the most likely of anytime to have students move back to school.

The purpose of this research is to see how college move-in affects gasoline prices. To discover the effect, a difference-in-difference regression was created using a fixed effects equation. The equation with fixed effects would compare the average price of all the stations in a city in the data on the move-in day with the average price in other cities that do not have move-in on that day. This method would thus show the difference in prices on move-in affected stations from unaffected stations, essentially creating a difference-in-difference regression. To do this, we set up our regression as a panel data set. We regress price on city fixed effects, date fixed effects, and a dummy variable for the move-in day. The city fixed effects is included because we wanted to control for any difference in prices based on properties unique to each city. The date fixed effects was included to control for any seasonal price patterns. In this way, we were able to separate any differences in daily prices because of seasonal patterns from the actual move-in effect.

The Regressions/ Results

For the first regression, we wanted to see what the prices in cities generally did on the move-in day. What we found (see Figure 1), using the difference-in-difference method listed above, was a positive and significant result, where the coefficient indicates that the move-in caused a three-cent increase in prices on the move-in day compared to cities without move-in on those days. While the rise is not gargantuan, it does still show strong support for rising gasoline prices during the move-in. In case there was any autocorrelation bias in the results, clustered standard errors were used that are robust to serial correlation within a given city. What was found (Figure 2) was an even more significant coefficient. These results provide even more evidence for increased prices on the move-in day.

For our next regression we wanted to see how the days around the move-in day looked. It might be expected to see a spike in prices around the move-in day that would die off soon after the day. Since the parents would leave soon after moving their children to the campus, it could be reasonable to assume that prices return to a normal level. However, the next regression (Figure 3) fairly clearly shows this to not be the case. In this regression, the price was also regressed on dummy variables for each of the days leading up to the move-in and on each of the days following it. What these results show are an extended move-in effect that spanned from at least six days prior to the actual move-in through to about eighteen days after the move-in. Almost all of the days listed in the regression are decreasingly positive and significant, depending on the length of time that has passed since the move-in.

That the move-in effect lasted for over two weeks after the move-in, while not expected, is not too surprising. There are students that actively drive while in school, and it is likely that those students that do not come from the campus city will not know the gasoline price dispersion any more than their parents. One explanation for the longer move-in effect could be that it represents the time that it took students to learn the prices. An explanation for why the move-in effect was affecting prices before the move-in day could be that campuses are active prior to the move-in. Campuses do not suddenly come to life on the move-in day, but are teeming with events and people for days prior. That people are already on campus days before the move-in could lead gasoline firms to raise prices sooner than the official move-in day. While the results do not definitively answer any causality questions, they do clearly show a protracted, positive move-in effect.

In our next regression, we wanted to see how the distance of each station from the university affected the move-in effect. To do this we included distance fixed effects in the regression and used station fixed effects instead of city fixed effects. Now we were measuring the price difference of stations not affected by the move-in from those that were. The results (see Figure 4) show the impact of the move-in on prices for stations at the given distances. The data shows that all the coefficients were positive and did not decrease with distance. In fact the effect appears to get bigger after the first few miles from campus. The strongest coefficients that we see are actually the farthest from the campus; however, this may not be that surprising because of the small amount of stations that are that far from campus in our data set, which could bias the results. For example, some schools may only have had two gasoline stations farther than seven miles from campus. Regardless, this regression shows that the move-in effect was not restricted to only very local stations in the city, which suggests that gasoline buyers were just as likely to purchase their gas close to the station as they would be to go farther from campus.

For our final regressions, we wanted to see how the size of the school impacted the increase in prices. We expected to find that the larger the student body, the greater the impact on the prices. We used the same approach as we did with the city average price regressions, but we used three dummy variables that indicated the size of the student body. Large schools were identified as having student bodies larger than thirty thousand students. Schools with under 15000 students were labeled small, and the schools larger than small schools but smaller than large schools were designated as medium. Our results (Figures 5) show some support for our expectations. All three were decreasingly positive with size and significance. However, the difference between even the big schools and the small schools was found to not be very significantly different. Overall, there may have been some difference between large schools and small schools, but the difference was not very substantial.

Conclusion

In our research, we have tried to see the effect that college move-in day would have on gasoline prices. The literature presented showed that there were multiple explanations for what gasoline prices could do in the face of an increase in demand. We set up multiple difference-in-difference regressions to discover the move-in effect. The results from the regressions strongly suggest that the price of gasoline did increase on the official move-in day. In fact, it was shown that gasoline prices remained high for at least a week before the move-in day and for over two weeks after the move-in.

Future research on the impact of demand spikes on the gasoline price market could look at the move-in date after winter break and the effect from home football games. Other research should look more closely at whether these effects could be the result specific economic models such as the supply and demand model or the tourists-natives model.

Figures
*** Significance at the 95% level**

Figure 1

Variable	Coefficient	Standard Error
Move-in Day	3.00461*	.9080607

Figure 2

Variable	Coefficient	Robust Standard Error
Move-in Day	3.00461*	.7288254

Figure 3

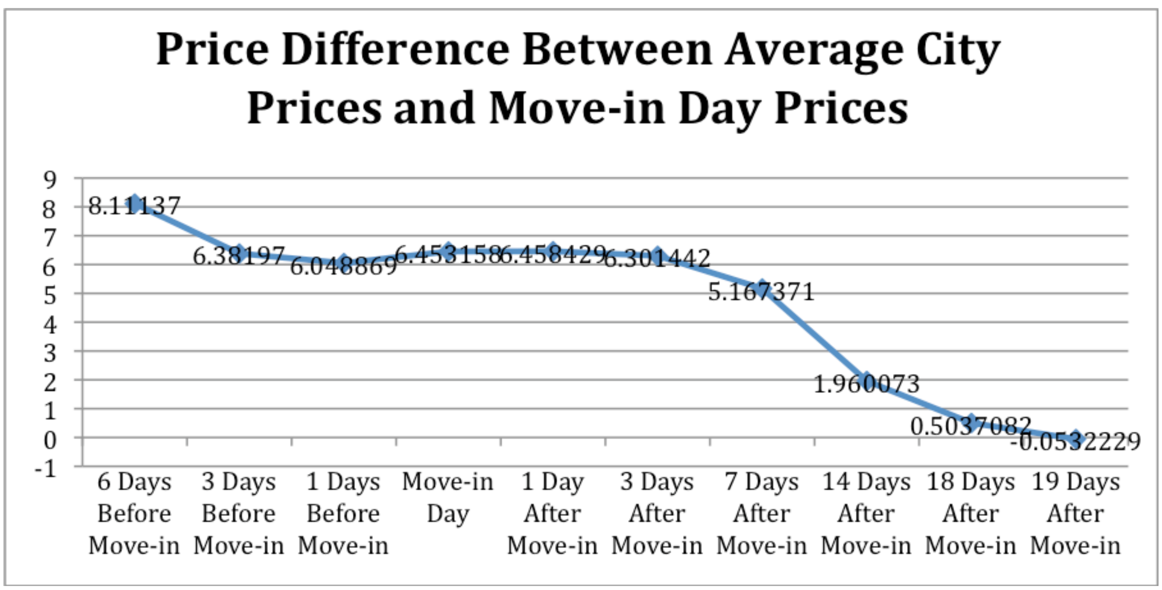

Figure 4

Move-in Variable	Coefficient	Standard Error
< 1 Mile from Campus	2.044859*	.6751924
Between 1 and 2 Miles from Campus	2.479205*	.4234885
Between 2 and 3 Miles from Campus	2.854186*	.4489102
Between 3 and 4 Miles from Campus	3.405022*	.5575168
Between 5 and 6 Miles from Campus	3.776274*	.952062
Between 6 and 7 Miles from Campus	1.99544	1.066782
Between 7 and 8 Miles from Campus	3.48658*	1.015433
Between 8 and 9 Miles from Campus	2.724438*	.9434634
Between 9 and 10 Miles from Campus	7.503769*	1.162193
>10 Miles from Campus	7.972022*	2.677116

Figure 5

Size of School Variable	Coefficient	Robust Standard Error
Big	3.896346*	1.685333
Medium	3.278125*	1.1547
Small	2.285548*	.6551367

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[i] It has been documented inside the Midwest that gasoline stations and markets are structured differently than in other places throughout the US. What results is a highly volatile price cycle that would make it difficult to separate the move-in effect from these variations. For more information on these Midwestern gasoline price cycles, see Lewis, Price Leadership and Coordination in Retail Gasoline Markets with Price Cycles. 2009.

[ii] It was originally over 70, but the move-in dates for some of the schools were before our data set began.

[iii] http://itouchmap.com/latlong.html

[iv] http://autos.msn.com/everyday/gasstations.aspx

[v] For some of the selected schools, there just were not thirty gasoline stations close to the school. In these circumstances, less than thirty stations were acceptable.

[vi] We only removed stations with less than 30 observations, or, one third of the total possible number of observations.

[vii] http://www.appstate.edu http://www.asu.edu/ http://www2.astate.edu/ http://www.baylor.edu/
http://www.boisestate.edu/ http://www.byu.edu/webapp/home/index.jsp
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